

**Automated extraction of absorption features from  
Airborne Visible/Infrared Imaging Spectrometer  
(AVIRIS) and Geophysical and Environmental Research  
Imaging Spectrometer (GERIS) data**

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**ABSTRACT**

Automated techniques have been developed for the extraction and characterization of absorption features from reflectance spectra. The absorption feature extraction algorithms have been successfully tested on laboratory, field, and aircraft imaging spectrometer data. A suite of laboratory spectra of the most common minerals has been analyzed and absorption band characteristics tabulated. A prototype expert system has been designed, implemented, and successfully tested to allow identification of minerals based on the extracted absorption band characteristics. AVIRIS spectra for a site in the northern Grapevine Mountains, Nevada, have been characterized and the minerals sericite (fine grained muscovite) and dolomite have been identified. The minerals kaolinite, alunite, and buddingtonite have been directly identified and mapped for a site at Cuprite, Nevada, using the feature extraction algorithms on the new Geophysical and Environmental Research 64 channel imaging spectrometer (GERIS) data. The feature extraction routines (written in FORTRAN and C) have been interfaced to the expert system (written in PROLOG) to allow both efficient processing of numerical data and logical spectrum analysis.

**INTRODUCTION**

Aircraft imaging spectrometers measure light reflected from the Earth's surface, utilizing many narrow contiguous spectral bands to construct detailed reflectance spectra for millions of discrete picture elements (pixels) (Goetz and others, 1985). One difficulty confronting researchers is that the immense volume of data collected by these systems prohibit detailed manual analysis. The objective of this work is to develop automated techniques for analysis of imaging spectrometer data that emulate the analytical processes used by a human observer. These techniques must

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efficiently use available computing power to complete the analysis in a reasonable period of time.

### FEATURE EXTRACTION

Techniques for extraction of spectral features from field and laboratory reflectance spectra have been in use for several years (Green and Craig, 1985; Kruse and others, 1986; Yamaguchi and Lyon, 1987; Clark and others, 1987). We are developing computer automated spectral feature extraction algorithms (implemented in FORTRAN and C) that allow extraction and subjective characterization of laboratory, field, and imaging spectrometer spectra (Kruse and others, 1986; Kruse, 1987, 1988a, 1988b). The absorption feature information is extracted from each spectrum using the following techniques. The computer rapidly identifies maxima in the spectrum and fits a continuum of straight line segments between these points. The continuum is removed from the data using division. The minima of the continuum-removed spectrum are determined and the 10 strongest features are extracted. The wavelength position, depth, full width at half the maximum depth (FWHM), and asymmetry for each of these 10 features are then determined and tabulated.

A fast, simple approach was chosen to fit the continuum. First, high points of the spectrum are determined using magnitude and slope criteria. The magnitude of the reflectance value of a high point must be larger than the average reflectance on either side. The exact number of points used in the average is determined by using a percentage of the total number of channels. The averaging procedure aids in the detection of band shoulders. In addition, the slope to the left of the high point must be positive and the slope on the right must be negative. Once the high points are located, straight line segments are drawn between them. Then for every point in the spectrum the actual reflectance and the line segment reflectance are compared. The reflectance value of the continuum at any given point is defined as the larger of these two values (Figure 1, Table 1). The advantage of this simple approach is that only a single pass through the spectrum is required to characterize the continuum.

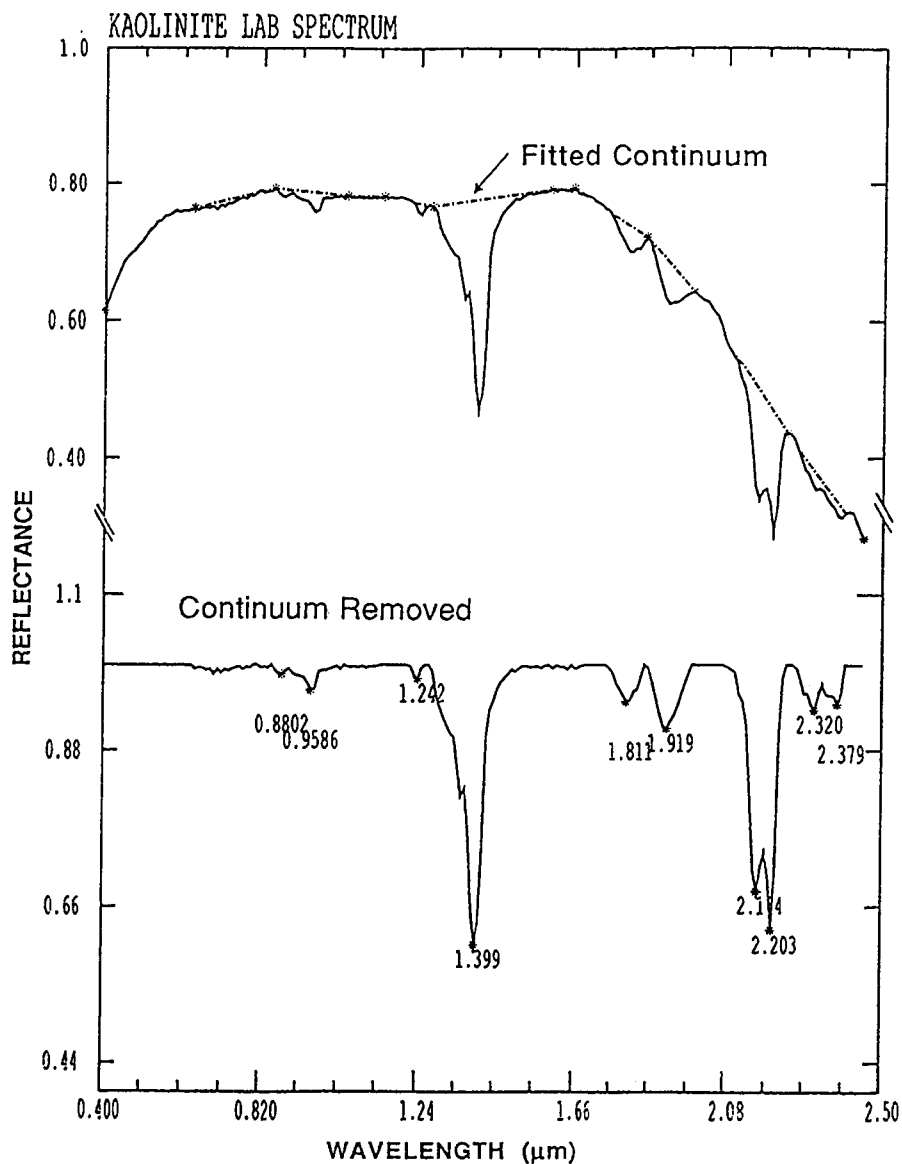


Figure 1. Laboratory spectrum of kaolinite showing fitted continuum, and continuum removed spectrum. (Lab spectrum from the USGS, Denver spectral library).

ABSORPTION BAND ANALYSIS FOR KAOLINITE LAB SPECTRUM

Band	Order	Wave	Depth	FWHM	Asym
1	1/1	1.3996	0.3939	0.0588	0.6170
2	1/2	2.2032	0.3732	0.0784	0.2161
3	2/2	2.1640	0.3184	0.0000	0.0000
4	1/1	1.9190	0.0895	0.0686	1.2802
5	1/2	2.3208	0.0627	0.0588	1.8101
6	2/2	2.3796	0.0542	0.0000	0.0000
7	1/1	1.8112	0.0511	0.0686	1.1634
8	1/1	0.9586	0.0352	0.0392	0.5126
9	1/1	1.2428	0.0189	0.0294	0.2628
10	1/1	0.8802	0.0130	0.0490	10.3361

Table 1. Absorption band analysis for kaolinite lab spectrum.

Minima are located using the inverse of the criteria for determining maxima. Given a minimum depth threshold, the 10 features with the greatest depths are determined. For each of these 10 features, the wavelength position of the minimum is determined as well as the FWHM (Figure 2). If more than one minima lies between two high points then the band is defined as being a multiple band. Band "order" indicates the number of bands in the multiple band and the relative depth of the band compared with the other members of the multiple band. The asymmetry is defined as the sum of the reflectance values for feature channels to the right of the minimum divided by the sum of the reflectance values for feature channels to the left. Symmetrical bands have an asymmetry value of one. Bands that are asymmetrical towards shorter wavelengths have asymmetry less than one, while bands that are asymmetrical towards longer wavelengths have asymmetry greater than one.

#### **EXAMPLES FROM NEVADA AVIRIS AND GERIS**

The continuum-removal and feature extraction procedures were used to analyze individual spectra from AVIRIS data for a site in the northern Grapevine Mountains, Nevada. Although these data have severe signal-to-noise problems, the feature extraction procedures successfully produced continuum-removed spectra that could be compared to laboratory spectra. Many of the features located in the AVIRIS data are noise, however, the strongest absorption bands correspond to bands in the laboratory spectra. Figures 3 and 4 show AVIRIS spectra for known areas of sericite (fine grained muscovite) and dolomite (Kruse, 1988a).

The feature extraction algorithms were also tested on Geophysical and Environmental Research Inc. 64 channel imaging spectrometer (GERIS) data from Cuprite, Nevada. This instrument is the first commercial imaging spectrometer. The GERIS collects data from 0.43 to 2.5  $\mu\text{m}$  in 64 channels of varying width. The 24 visible and infrared bands between 0.43 and 0.972  $\mu\text{m}$  are 23 nm wide, the 8 bands in the infrared between 1.08 and 1.8  $\mu\text{m}$  are 120 nm wide, and the 31 bands from 1.99 to 2.5  $\mu\text{m}$  are 16 nm wide (William Collins, written communication, 1988). Only the last 31 bands were used in this study. The feature extraction procedures were

# Continuum Removed - KAOLINITE LAB SPECTRUM

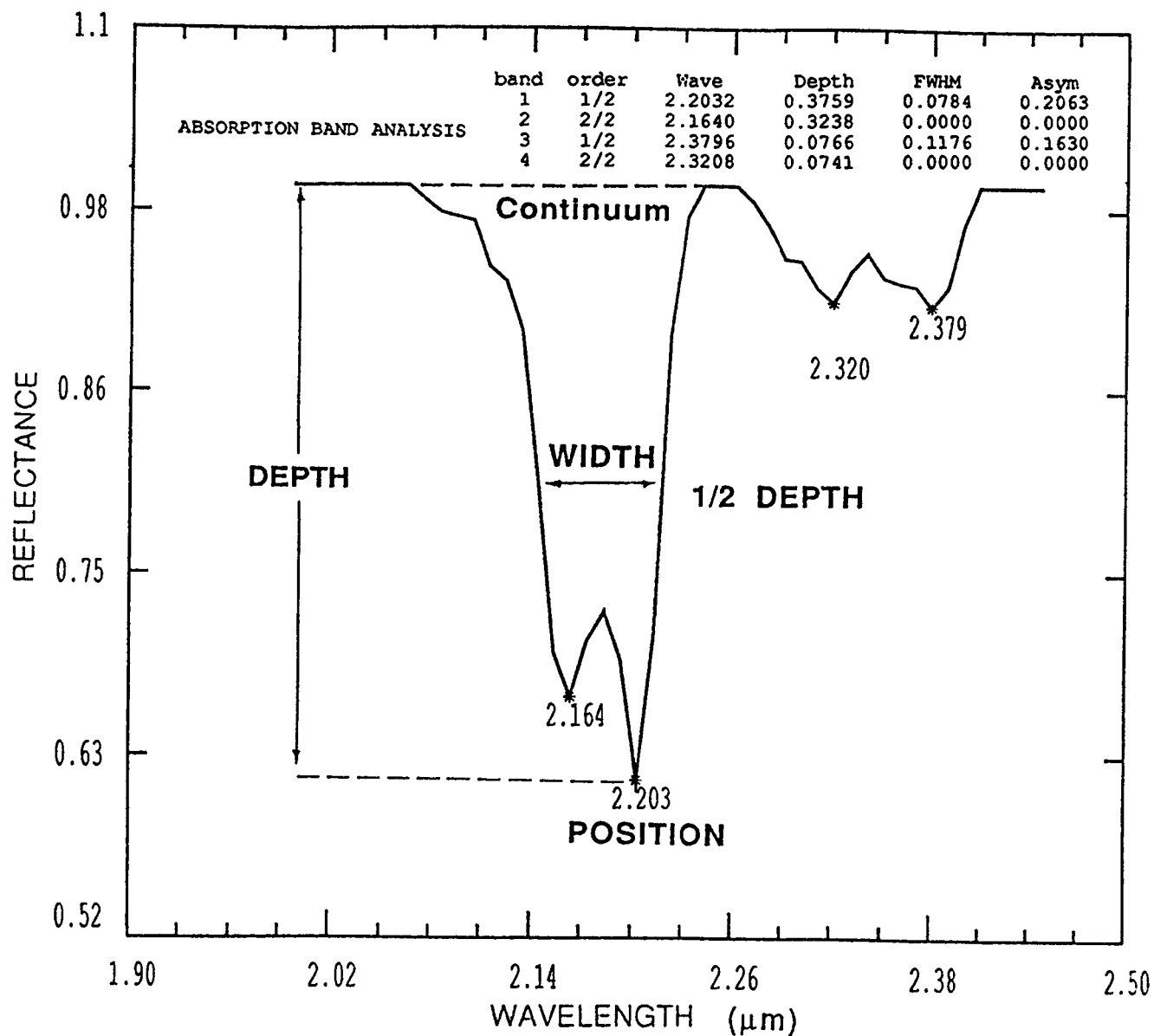


Figure 2 Laboratory spectrum of kaolinite showing the absorption band parameters position, depth, and width. (Laboratory spectrum is from the USGS, Denver spectral library.)

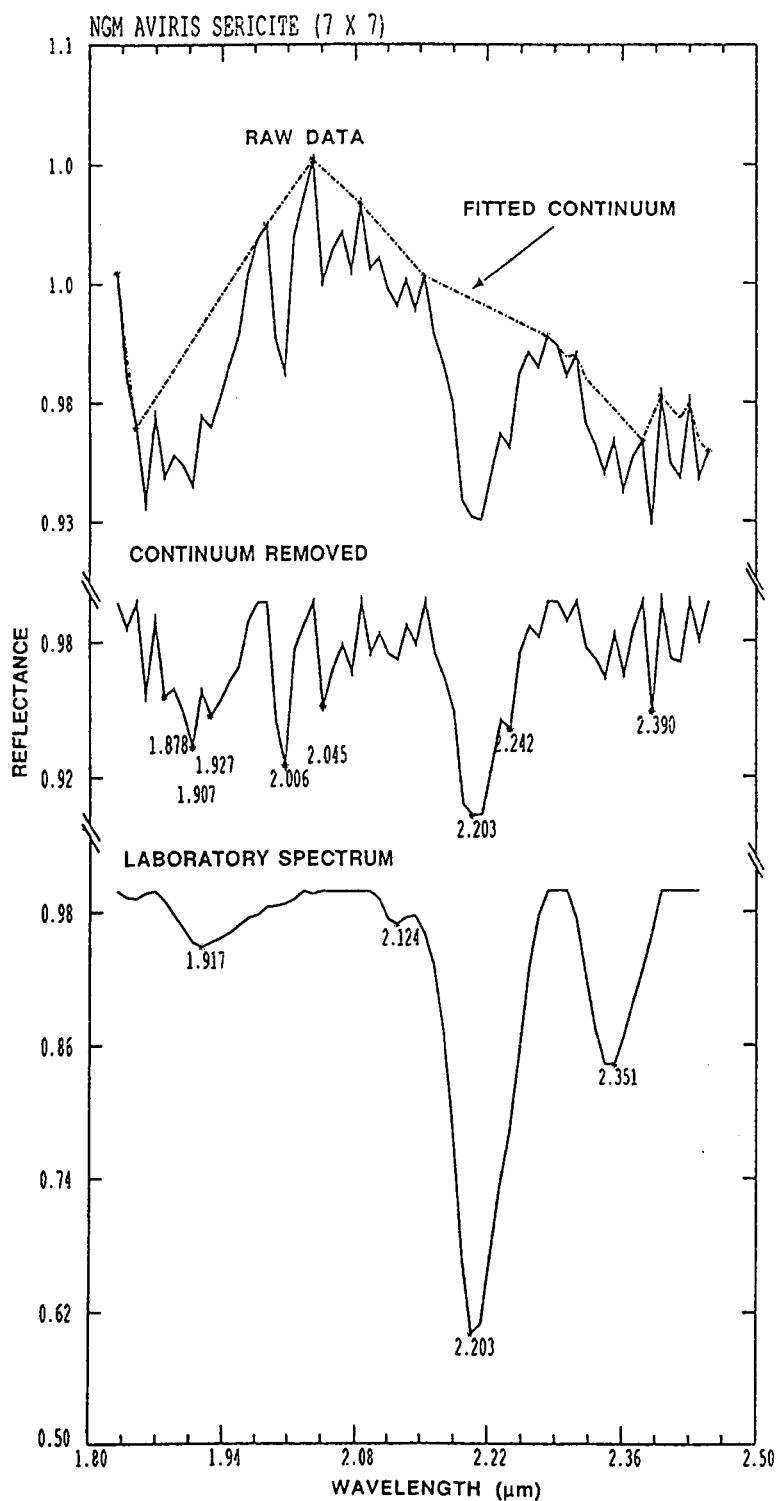


Figure 3. Raw and continuum-removed AVIRIS spectra for sericite (muscovite) from the northern Grapevine Mountains, Nevada, compared to a laboratory spectrum of muscovite. (Laboratory spectrum is from the USGS, Denver spectral library.)

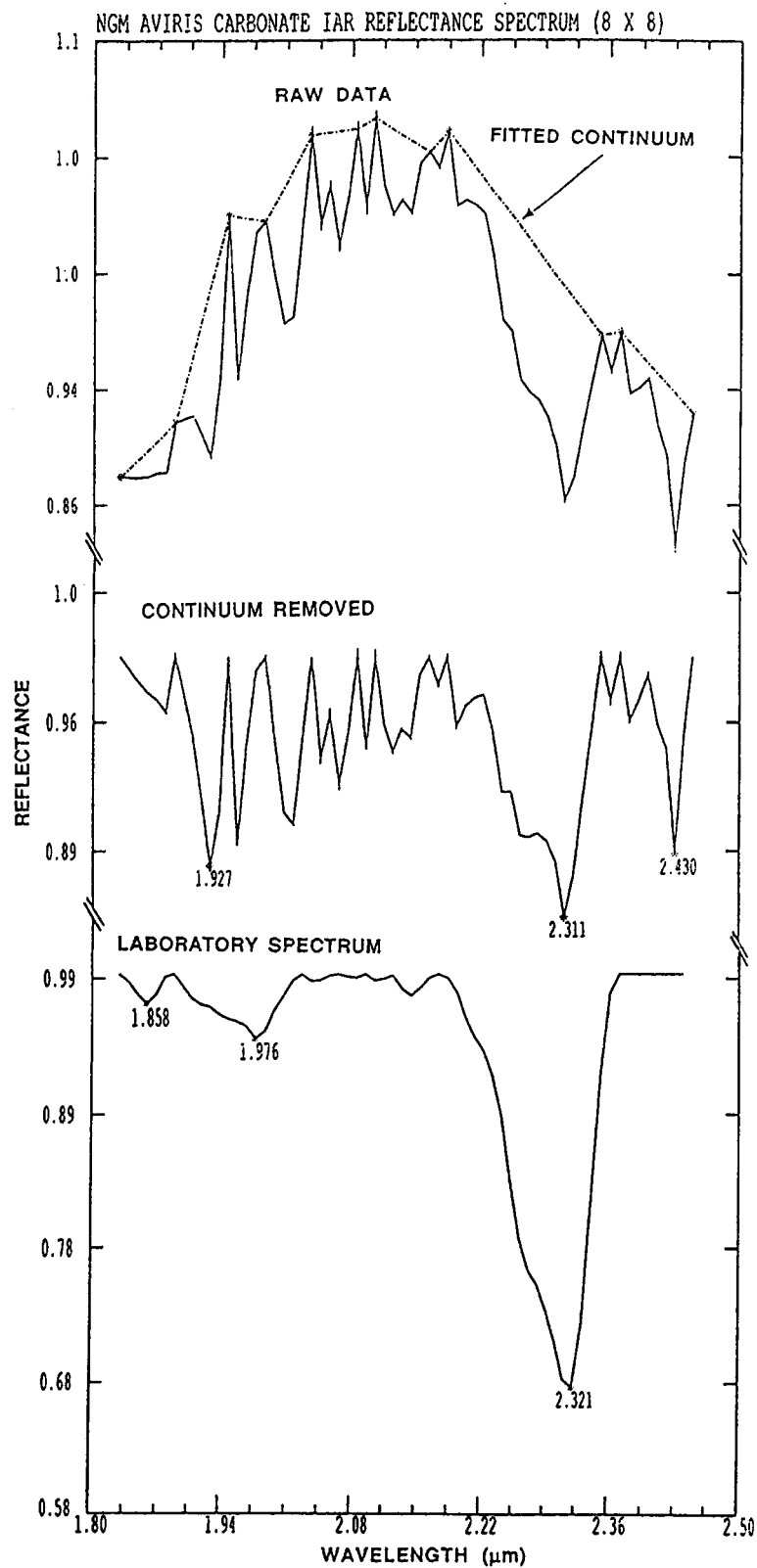


Figure 4. Raw and continuum-removed AVIRIS spectra for dolomite from the northern Grapevine Mountains, Nevada, compared to a laboratory spectrum of dolomite. (Laboratory spectrum is from the USGS, Denver spectral library.)

used to extract absorption band characteristics directly from the image data. Comparison of the continuum-removed GERIS spectra with laboratory spectra was used to identify kaolinite, alunite, and buddingtonite. An example of an alunite spectrum extracted from the GERIS data is shown in Figure 5 with a laboratory spectrum of alunite for comparison. Comparison of the tabulated absorption band characteristics are shown in Table 2.

### EXPERT SYSTEM

The second stage of this research uses facts and rules derived from the automated analysis of laboratory measurements of selected minerals to define a knowledge base that can be applied to analysis of reflectance spectra (Kruse, 1988b). The five parameters derived using the feature extraction procedure were used to derive the facts and rules utilized in the expert system. The knowledge base/expert system approach was chosen to minimize analysis time (Yamaguchi and Lyon, 1987; Goetting and Lyon, 1987). Other procedures under development (Clark and others, 1987) propose use of spectral library or feature library searching to determine a best match for a given spectrum. Analysis time required is proportional to the size of the library to be searched. The expert system approach reduces the analysis time by using a tree hierarchy (Figure 6). We are using the PROLOG programming language (Quintus Computer Systems, 1987) to implement the facts and rules in a logical fashion similar to the decision process followed by an experienced analyst. A decision is made at each level of the tree based on facts and rules derived through prior analysis of the spectral library. Critical absorption band characteristics for a given mineral are defined using the feature extraction procedure. Facts and rules are written for each mineral or group of minerals in the database. The spectral library itself is never accessed during the analysis of a spectrum.

The decision process followed by the computer is designed to emulate the logical steps followed by an experienced analyst. The strongest absorption feature for a given spectrum (or pixel) is determined, and the spectrum is broadly classified



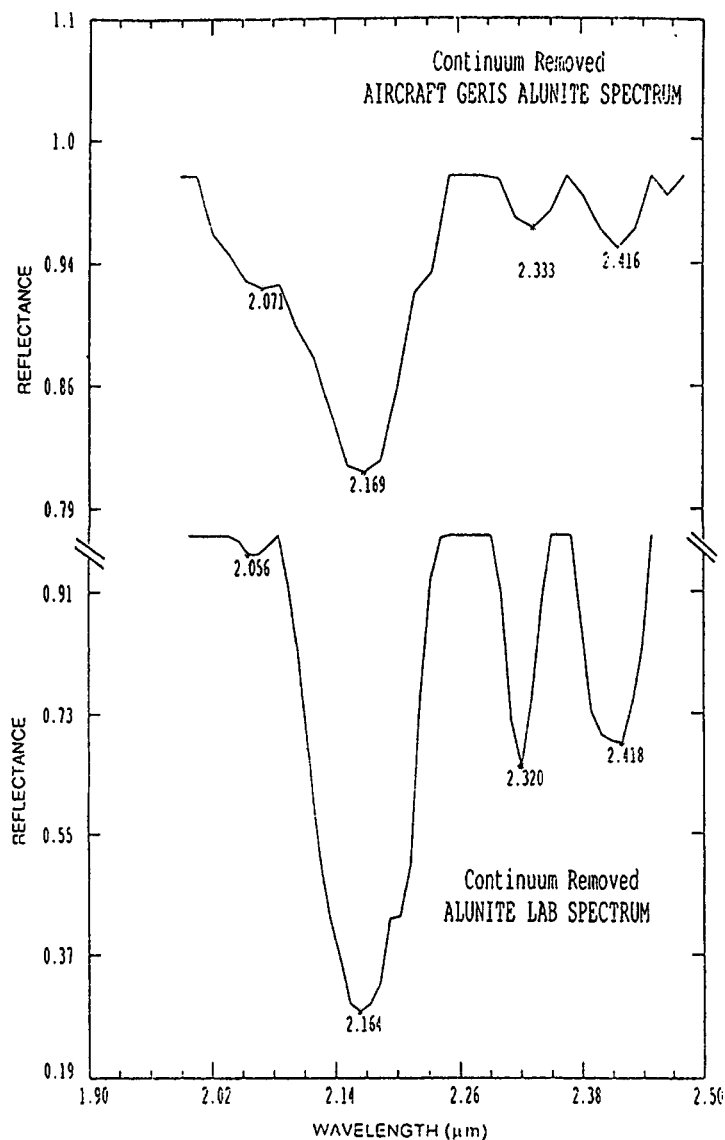


Figure 5. Comparison of GERIS and laboratory spectra of alunite.

Band	Order	Position	Depth	Width	Asymetry
1	1/2	2.1697	0.1855	0.1314	0.5337
2	2/2	2.0711	0.0712	0.0000	0.0000
3	1/1	2.4161	0.0451	0.0657	0.7278
4	1/1	2.3340	0.0325	0.0657	0.7756

Band	Order	Position	Depth	Width	Asymetry
1	1/1	2.1640	0.7057	0.1078	1.1114
2	1/1	2.3208	0.3422	0.0392	0.9432
3	1/1	2.4188	0.3074	0.0686	0.4155
4	1/1	2.0562	0.0278	0.0392	5.6839

Table 2. Comparison of absorption band parameters for GERIS and laboratory spectra of alunite.

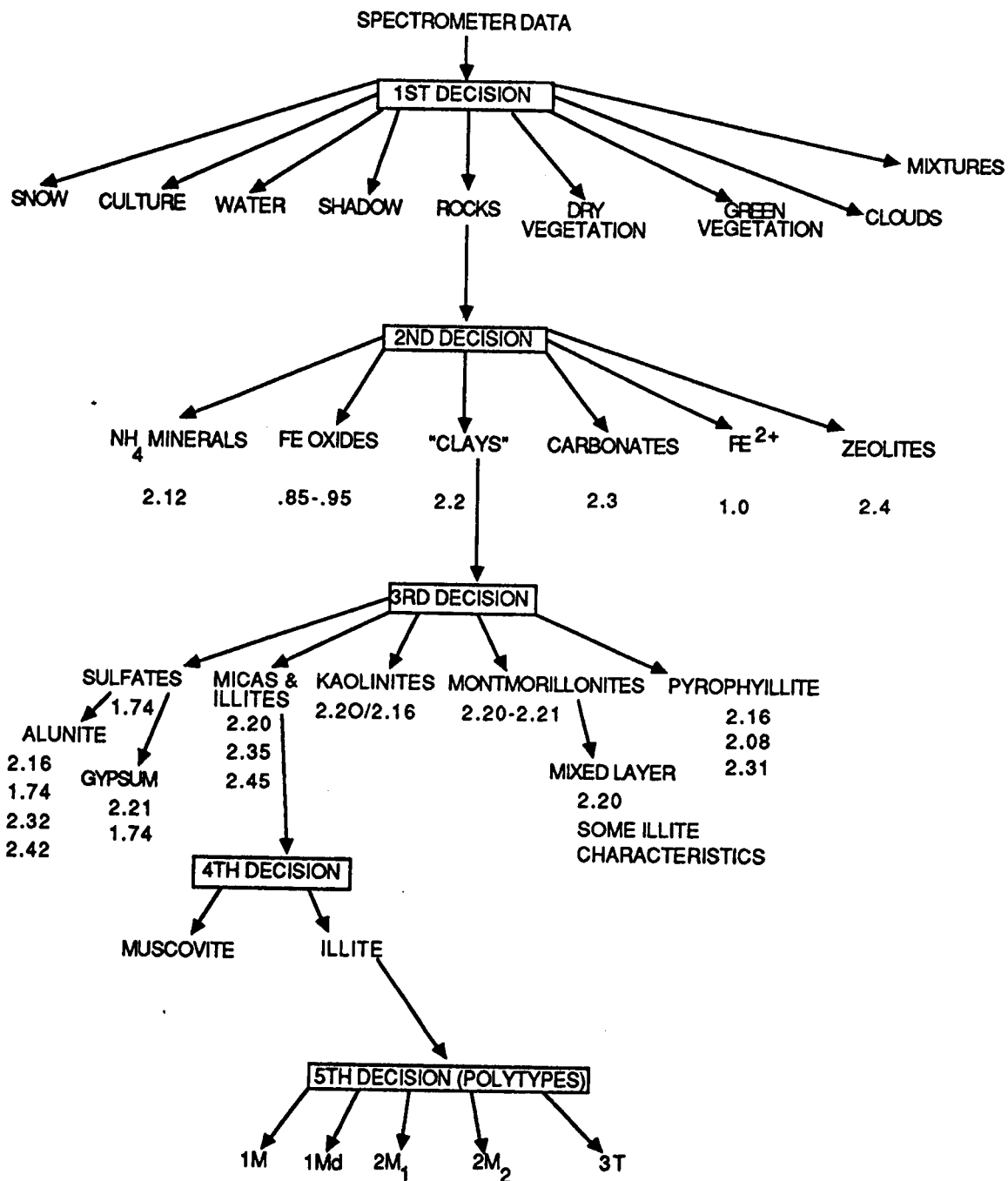


Figure 6. Prototype expert system decision tree.

(eg. clay, carbonate, iron oxide). Primary band characteristics (eg. doublet, triplet) and secondary/tertiary absorption bands are used to progress through the tree structure until an identification is made. If the decision process fails because there is insufficient information to identify a specific mineral, then the last classification is used to give the best answer possible. A comparison of two continuum-removed spectra and an example of the decision process is shown in Figures 7 and Table 3 and Figure 8.

### CONCLUSIONS

An absorption feature extraction procedure and prototype expert system have been developed that allow rapid analysis of reflectance spectra and identification of minerals. Numerical processing of the spectral data is optimized in FORTRAN and C. Logical decisions based on facts and rules derived from analysis of laboratory spectra are implemented in PROLOG. The combination of the numerical and logical processing routines takes advantage of the inherent strengths of the associated computer languages to efficiently analyze the data. The feature extraction techniques and expert system have been successfully tested on laboratory, field, and imaging spectrometer data. Additional minerals need to be added to the database, and facts and rules must be refined to fully utilize the expert system for mineral identification. Future efforts will concentrate on integrating the knowledge base into an image processing environment for analysis of entire AVIRIS and GERIS images.

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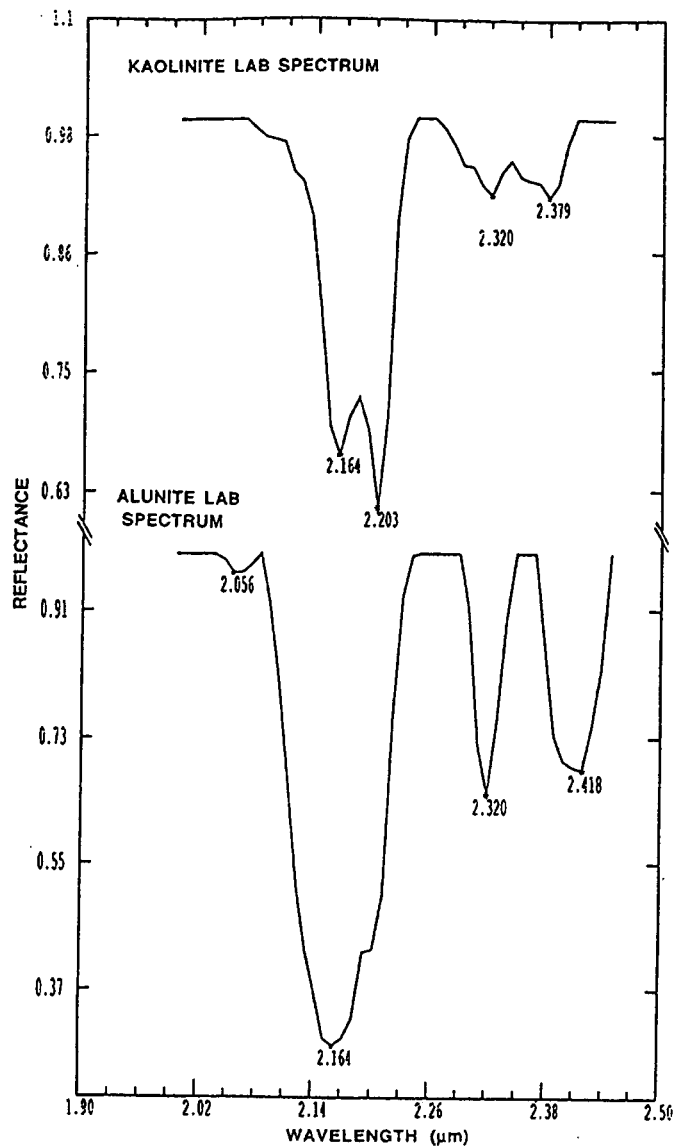


Figure 7. Comparison of kaolinite and alunite lab spectra.

ABSORPTION BAND ANALYSIS for KAOLINITE LAB SPECTRUM

<u>Band</u>	<u>Order</u>	<u>Position</u>	<u>Depth</u>	<u>Width</u>	<u>Asymetry</u>
1	1/2	2.2032	0.3759	0.0784	0.2063
2	2/2	2.1640	0.3238	0.0000	0.0000
3	1/2	2.3796	0.0766	0.1176	0.1630
4	2/2	2.3208	0.0741	0.0000	0.0000

ABSORPTION BAND ANALYSIS for ALUNITE LAB SPECTRUM

<u>Band</u>	<u>Order</u>	<u>Position</u>	<u>Depth</u>	<u>Width</u>	<u>Asymetry</u>
1	1/1	2.1640	0.7057	0.1078	1.1114
2	1/1	2.3208	0.3422	0.0392	0.9432
3	1/1	2.4188	0.3074	0.0686	0.4155
4	1/1	2.0562	0.0278	0.0392	5.6839

Table 3. Comparison of absorption band parameters for kaolinite and alunite lab spectra.

## **Example : kaolinite vs. alunite.**

1st Decision - predetermined to be "ROCK"

2nd Decision ( rock level )

**if** it has a deep band in 2.15-2.22  $\mu\text{m}$  region  
**then** look for in "clay" species.

3rd Decision ( "clay" species )

**if** it has a doublet near 2.2  $\mu\text{m}$   
    and strongest band of the doublet is 2.2  $\mu\text{m}$   
    and weakest band of the doublet is near 2.16  
**then** it is **kaolinite**.

**if** it has a single band near 2.2  $\mu\text{m}$   
    and a weaker band near 2.32  $\mu\text{m}$   
    and a weaker band near 2.42  $\mu\text{m}$   
**then** it is **alunite**.

Figure 8. Example of decision process for discriminating kaolinite from alunite.

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